Full title: The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis.

Running heading: Internal–external load relationships in team sports.

Authors: Shaun J. McLaren[1,2], Tom W. Macpherson[1], Aaron J. Coutts[3], Christopher Hurst[1], Iain R. Spears[4], Matthew Weston[1].

Affiliations: [1]Department of Psychology, Sport & Exercise, School of Social Sciences, Humanities and Law, Teesside University, Middlesbrough, United Kingdom.

[2]Sport Science and Medical Department, Hartlepool United Football Club, Hartlepool, United Kingdom.

[3]Sport and Exercise Discipline Group, Faculty of Health, University of Technology Sydney (UTS), Sydney, Australia.

[4]Pro-Football Support, Huddersfield, United Kingdom.

ORCID Identifiers: Shaun J. McLaren: 0000-0003-0480-3209

Tom W. Macpherson: 0000-0002-6943-7302

Aaron J. Coutts: 0000-0002-1782-7691

Christopher Hurst: 0000-0002-7239-6599

Iain R. Spears: 0000-0003-4982-2841

Matthew Weston: 0000-0002-9531-3004

Corresponding Author:

Shaun J. McLaren.
Department of Psychology, Sport and Exercise,
School of Social Sciences, Humanities and Law,
Teesside University,
Middlesbrough.
TS1 3BA.
UNITED KINGDOM.
E: s.mclaren@tees.ac.uk

ABSTRACT

Background: The associations between internal and external measures of training load and intensity are important in understanding the training process and the validity of specific internal measures.

Objectives: We aimed to provide meta-analytic estimates of the relationships, as determined by a correlation coefficient, between internal and external measures of load and intensity during team-sport training and competition. A further aim was to examine the moderating effects of training mode on these relationships.

Data Sources: Six electronic databases (Scopus, Web of Science, PubMed, MEDLINE, SPORTDiscus, CINAHL) were searched for original research articles published up to September 2017. A Boolean search phrase was created to include search terms relevant to team-sport athletes (population; 37 keywords), internal load (dependent variable; 35 keywords) and external load (independent variable; 81 keywords).

Study Selection: Articles were considered for meta-analysis when a correlation coefficient describing the association between at least one internal and one external measure of session load or intensity, measured in the time or frequency domain, was obtained from team-sport athletes during normal training or match-play (i.e. unstructured observational study).

Data Extraction: The final data sample included 122 estimates from 13 independent studies describing 15 unique relationships between 3 internal and 9 external measures of load and intensity. This sample included 295 athletes and 10418 individual session observations. Internal measures were session ratings of perceived exertion (sRPE), sRPE training load (sRPE-TL) and heart-rate-derived training impulse (TRIMP). External measures were total distance (TD), the distance covered at high- and very-high speeds (HSRD; ≥ 13.1–15.0 km·h^{-1}, and VHSRD; ≥ 16.9–19.8 km·h^{-1}, respectively), accelerometer load (AL) and the number of sustained impacts (Impacts; > 2–5 G). Distinct training modes were identified as either Mixed (reference condition), Skills, Metabolic or Neuromuscular.

Data Analysis: Separate random effects meta-analyses were conducted for each dataset (n = 15) to determine the pooled relationships between internal and external measures of load and intensity. The moderating effects of training mode were examined using random-effects meta-regression for datasets with ≥ 10 estimates (n = 4). Magnitude-based inferences were used to interpret analyses outcomes.

Results: During all training modes combined, the external load relationships for sRPE-TL were possibly very large with TD (r = 0.79; 90% confidence interval 0.74 to 0.83), possibly large with AL (0.63; 0.54 to 0.70) and Impacts (0.57; 0.47 to 0.64), and likely moderate with HSRD (0.47; 0.32 to 0.59). The relationship between TRIMP and AL was possibly large (0.54; 0.40 to 0.66). All other relationships were unclear or not possible to inference (r range = 0.17 to 0.74, n = 10 datasets). Between-estimate heterogeneity (SDs representing unexplained variation; τ) in the pooled internal–external relationships were trivial to extremely large for sRPE (τ = 0.00 to 0.47), small to large for sRPE-TL (τ = 0.07 to 0.31), and trivial to moderate for TRIMP (τ = 0.00 to 0.17). The internal–external load relationships during Mixed training were possibly very large for sRPE-TL with TD (0.82; 0.75 to 0.87) and AL (0.81; 0.74 to 0.86), and TRIMP with AL (0.72; 0.55 to 0.84), and possibly large for sRPE-TL with HSRD (0.65; 0.44 to 0.80). A reduction in these correlation magnitudes was evident for all other training modes (range of the change in r when compared with Mixed training = -0.08 to -0.58), with these differences being unclear to possibly large. Training mode explained 25–100% of the between-estimate variance in the internal–external load relationships.

Conclusion: Perceived-exertion- and heart-rate-derived measures of internal load show consistently positive associations with running- and accelerometer-derived external loads and intensity during team-

sport training and competition, but the magnitude and uncertainty of these relationships are measure and training mode dependent.

KEY POINTS

- Total running distance has the strongest association with sRPE, sRPE-TL and TRIMP during team-sport training and competition.
- External load relationships appear stronger for sRPE-TL when compared with TRIMP.
- Internal–external load relationships differ depending on the mode of training.

1.0 INTRODUCTION

The training process describes the systematic and periodized application of physiological and biomechanical stress in pursuit of functional training outcomes [1]. The development or maintenance of fitness and the potentiation of biomotor abilities are two such outcomes that are important to prepare intermittent team-sport athletes for the frequent and substantial demands of competition [2]. Such adaptations are determined by a combination of training volume, intensity and frequency [3], collectively referred to as training load [4]. Moderate to high training loads are required to drive positive training-induced adaptations, yet may increase the likelihood of fatigue, impaired wellbeing, injury or illness [5-8]. Indeed, the relationships between training load and training outcomes have been systematically reviewed [9-12], with moderate evidence supporting the benefits and risks associated with high and also low training loads. The quantification and monitoring of training load is therefore an important aspect of athlete management [5-7,13,14] and has the potential to provide practitioners and coaches with an objective framework for evidence-based decisions [15-17].

Training load encompasses both external and internal dimensions, with external training loads representing the physical work performed during the training session or competition and internal training loads being the associated biochemical (physical and physiological) and biomechanical stress responses [1,18]. Acute and chronic changes in the training outcome are ultimately the result of an athlete's cumulative internal load over a given time period [1,3,18], which therefore places great importance on the measurement of internal load and its influencing factors. It is understood that greater external loads, particularly those common to the stochastic demands of team-sport training and competition, increase metabolic energy costs and soft tissue force absorption/production [18], thereby increasing internal loads. This acute dose–response paradigm forms the basis of training theory [1] and is important for understanding the specific internal responses associated with various external training doses [19]. A knowledge of the relationships between internal and external training loads therefore has the potential to enhance training prescription, periodization and athlete management through a detailed assessment of training fidelity and efficacy [17,19-21]. As an adjunct to this, internal–external load relationships can provide evidence for the construct validity and sensitivity of specific internal load indicators [22], which is important in absence of any 'gold-standard' criterion measure.

The relationships between internal and external loads in team-sport athletes have received much attention to date, with a myriad of studies reporting correlation magnitudes ranging from trivial to very large [19,22-36]. The dispersion in these effect sizes would suggest that internal–external load relationships are not yet fully understood, which has led some authors to question the validity of specific internal load measures [37,38]. These findings may be a consequence of the varied training typologies observed in previous research, suggesting that exercise structure, goals, activities and work-rest ratios could reasonably influence the relationships between internal and external loads. Given that team-sport athletes regularly undertake a diverse range of training activities [22,31], the effects of training mode on internal–external load relationships would appear important in understanding the training process and the measurement of internal training load. An appropriate synthesis of the current literature to date is therefore timely. Accordingly, the aims of our meta-analysis were to establish pooled estimates of the relationships between internal and external loads during intermittent team-sport training and competition, while also exploring the putative moderating effects of training mode.

2.0 METHODS

2.1 Search Strategy

This review was carried out in accordance with the ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses’ (PRISMA) guidelines [39]. A search of six electronic databases (Scopus, Web of Science, PubMed, MEDLINE, SPORTDiscus, CINAHL) was conducted independently by two of the authors (SJM, TWM) to identify original research articles published from the earliest available records up to September 2017. The authors were not blinded to journal names or manuscript authors. We created a Boolean search phrase to include search terms relevant to team-sport athletes (population), internal load (dependent variable) and external load (independent variable). Relevant keywords for each search term were determined through pilot searching (screening of titles/abstracts/key words/full texts of previously known articles). Keywords were combined within-terms using the ‘OR’ operator and the final search phrase was constructed by combining the three search terms using the ‘AND’ operator (Table 1).

2.2 Screening Strategy and Study Selection

To select relevant articles, two of the authors (SJM, TWM) independently exported the electronic search results to an Excel spreadsheet (Microsoft Excel, Microsoft, Redmond, USA). Duplicate records were identified and removed before the remaining records were screened against the inclusion-exclusion criteria using a hierarchical approach (Table 2). We chose to omit any studies whose mean athlete age was ≤18 years old or otherwise defined as ‘adolescents’, ‘juniors’, ‘youth’ or ‘children’, as shifts in cognitive development (between the preoperational and formal intelligence stages) may influence the accuracy in ratings of perceived exertion (RPE) [40]. This also allowed us to maximise the likelihood that athletes included in our analyses were fully habituated with the entire range of sensations that correspond to each category of effort within the RPE scales (i.e. ‘anchoring’) [41,42]. In agreement with modern psychophysical theory [42], we chose to only include studies that employed level-anchored semi-ratio scales (i.e. Borg CR10® and CR100®) for the assessment of session RPE (sRPE) [43]. Studies using bespoke or modified scales, or those using non-category-ratio scales (e.g. Borg 6–20 RPE scale®), were therefore excluded. Accordingly, articles were considered for meta-analysis when a correlation coefficient describing the association between at least one internal and one external measure of session load or intensity, measured in the time or frequency domain, was obtained from team-sport athletes during normal, non-manipulated, training or match-play (i.e. unstructured observational study).

Titles and abstracts were initially screened and excluded against criteria 1–7 where applicable (Table 2). Full texts of the remaining papers were then accessed and screened against inclusion criteria 1–10 to determine their final inclusion-exclusion status. The reference lists of relevant review articles and eligible original research articles were also screened in an identical manner. The two author’s independent search results were then combined and any dispute on the final inclusion-exclusion status were resolved through discussion (n = 27). Following this selection process, there were 351 (28 of which had no numeric correlation coefficient reported) potential estimates from 18 independent studies that met our inclusion criteria (Figure 1).

2.3 Selection of Datasets and Estimates

In line with the aims of our meta-analysis and as a means of data reduction, we grouped internal and external measures of load and intensity based on their construct (e.g. heart-rate-derived training impulse [TRIMP]), rather than their specific measurement (e.g. Banister's [44], Edwards' [45], or individualised [46]). When a study reported more than one relationship describing the same internal and external construct, we elected to discard the estimates with the weakest correlation magnitude (n = 19 estimates). The typical (mean) difference in discarded versus retained data was trivial (r = 0.06, range = 0.01 to 0.23). We further identified five studies [22,23,26,27,35] meeting our inclusion criteria in which duplicate data were evident. To avoid the issue of double counting in our meta-analyses [47], we made informed decisions to discard these data based on our aims. One study [27] reported the relationships between sRPE training load (sRPE-TL) and three external load indicators using different measures of session volume in the calculation of sRPE-TL (i.e. total match duration, minutes played, and the addition of halftime and warm-up periods). To comply with the methodologies of our other included studies, we chose to only include estimates incorporating minutes played in the calculation of sRPE-TL (21 estimates removed). Another study [23] reported the relationships between internal and external measures of intensity during small-sided games of different formats (3 vs 3, 5 vs 5 and 7 vs 7) as well as the relationships for all formats combined. We chose to only include the relationships for all formats combined since no other study differentiated between variations of small-sided gameplay (36 estimates removed). A third study [22] reported the relations between internal and external loads and intensities for five discrete training modes (conditioning, skill-based conditioning, skills, speed and wrestling) as well as the pooled relationships for all training modes combined. We discarded the pooled estimates and retained the estimates from each training mode for our analyses (8 estimates removed). Finally, two studies [26,35] reported both within-athlete and partial correlations (i.e. the relationship between two variables while controlling for one or more other variables) for the same internal–external load relationships. Since no other studies meeting our inclusion criteria utilised partial correlations, we retained only the within-athlete correlations for our analyses (30 estimates removed). Of the remaining data, only datasets with two or more estimates from at least two independent studies were considered for meta-analysis (115 estimates, 107 datasets and 5 studies removed). This resulted in 15 final datasets containing 122 estimates (2 of which not reported) from 13 independent studies, with a total of 3 internal load/intensity measures and 9 external load/intensity measures (Table 4). Internal measures were sRPE, sRPE-TL and TRIMP. External measures were total distance (TD), the distance covered at high- and very-high speeds (HSRD and VHSRD, respectively), accelerometer load (AL) and the number of sustained impacts (Impacts).

2.4 Data Extraction

We sought to extract the Pearson's product moment correlation coefficient (r) and the associated sample size that described the internal–external load/intensity relationships for each estimate. Within-athlete correlations are recommended as the appropriate method for analysing repeated measures data [48], yet we faced the issue that some of our included studies employed a mixed correlation analyses—whereby all data are treat indiscriminately as a single sample [49]. This approach could be misleading when attempting to determine if higher external loads are associated with higher internal loads as the correlation magnitude may be influenced by between-athlete differences [48]. Re-analysis of indiscriminate correlation data and athlete-level meta-analysis were precluded on the presumption that our included studies' raw data would be under embargo from the clubs that samples were drawn [50]. Instead, we elected to assume that the between-athlete variability of internal and external loads is unlikely to outweigh the within-athlete variability over repeated observations [51,52], and the mixed-athlete correlation analyses from some of our included studies would therefore be free from violations of independence inherent in analysing repeated measures data [49]. In agreement with this and to mitigate the issue of disproportionate sample allocations [53], we specified the total number of athletes (as opposed to the total number of observations) as the sample size for each estimate within the meta-analyses. Accordingly, Pearson's product moment correlation coefficients were converted to Fisher's z values for analysis and subsequently back-converted for post-analysis interpretation. Fisher's z standard errors and variances were also calculated for estimate weightings and determination of uncertainty and heterogeneity in the pooled effects. Finally, we extracted descriptive information relating to the training activities performed in our included studies and categorised each estimate under one of the following four distinct training modes:

- **Mixed**: Field- or court-based training incorporating at least two of the training modes defined below. Competitive match-play is also categorised as mixed.
- **Skills**: Focus on enhancing sport-specific skills and team technical-tactical strategies.
- **Metabolic**: Intermittent small-sided games or high-intensity interval running, primarily aimed at improving players' aerobic fitness, prolonged high-intensity intermittent running ability and repeated effort ability.
- **Neuromuscular**: Speed, wrestle or strongman training, primarily aimed at improving players' force production, force transfer, movement and functional strength.

The corresponding authors of studies without the required data or where further clarity was necessary were contacted by email [19,22-26,29-32] and we received all relevant information from these studies. Graph digitizer software (DigitizeIt, Brainschweig, Germany) was used to obtain data from two studies where descriptive [28] and correlation [30] data were only available in figures. The final meta-analyses of the 15 datasets included 10418 individual session observations from 295 athletes. Descriptive information for the 13 studies included in our meta-analyses are displayed in Table 4.

2.5 Data Analysis

2.5.1 Publication Bias

To investigate the extent of publication bias in datasets with more than two estimates, we examined funnel plots of individual Fisher *z* values versus their corresponding standard errors for signs of asymmetrical scatter [54]. Asymmetrical scatter was evident in 1 (sRPE vs TD per min) of the 12 examined datasets (Supplementary File 1).

2.5.2 Meta-Analytic and Meta-Regression Models

Separate random effects meta-analyses were conducted for each dataset (n = 15) to determine the pooled internal–external load and intensity relationships. Uncertainty in the pooled correlation effects was expressed as 90% confidence intervals (CI), calculated using the Knapp and Hartung [55] approach. Between-estimate heterogeneity was then specified as an SD (Tau: τ) [56], calculated using DerSimonian and Laird's generalised method of moments [57]. Meta-regression was deemed possible when a dataset included ≥ 10 estimates [58]. We chose not to meta-regress the relationship describing sRPE-TL and Impacts as 11 of the 12 estimates came from 2 studies only. Accordingly, four separate random effects meta-regression models were conducted to explore the effects training mode on the pooled relationships of sRPE-TL with TD, HSRD and AL, and TRIMP with AL. Training modes were coded as dummy variables (categorical moderators) and their effects were evaluated as the difference between levels. We defined the reference condition for training mode as mixed team training, with the moderating effects of all other training modes expressed as the change in correlation magnitude by comparison to Mixed training. Uncertainty in these differences and between-estimate heterogeneity were expressed as 90% CI and τ, respectively, calculated as previously described. Finally, model strength was quantified as the proportion of between-estimate variance explained by training mode (i.e. unadjusted τ^2 vs fully adjusted τ^2; R^2_{Meta} [59]). All analyses were conducted using Comprehensive Meta-Analysis software, Version 3 (Biostat Inc., Englewood, NJ, USA).

2.5.3 Inferences

We used magnitude-based inferences [60,61] to provide a practical, real-world interpretation of our analyses. Correlation magnitudes and the effects of training mode were scaled against standardized threshold values of 0.10, 0.30, 0.50, 0.70 and 0.90 to represent small, moderate, large, very large and extremely large effects, respectively [54]. Effects were then evaluated mechanistically and deemed unclear if the 90% CI overlapped substantially positive and negative effect thresholds by a likelihood of ≥ 5% [54]. Otherwise, the chances of the true effect being at least that of the observed magnitude was interpreted using the following scale of probabilistic terms: 5–94.9%, possibly; 75–94.9%, likely; 95–99.4%, very likely; ≥ 99.5%, most likely [54]. Inferences were not possible for datasets with ≤ 3 estimates since the standard error of a Fishers z transformed correlation coefficient is equal to the inverse square root of $n-3$ [62]. Finally, to infer on the true unexplained variation in each relationship, we doubled the back-converted τ statistic before interpreting its magnitude [63] using the above scale of correlation effect sizes [54].

3.0 RESULTS

3.1 Relationships between Internal and External Measures of Load and Intensity

Forest plots displaying the weighted point estimates with 90% CI for each meta-analysis are available in Supplementary File 2. The meta-analysed relationships between internal and external loads and intensities are shown in Table 5. The direction of all pooled estimates was positive. Relationships with sRPE-TL were possibly very large with TD, likely large with AL and Impacts, and likely moderate with HSRD. The relationship between TRIMP and AL was possibly large. All other relationships were unclear or not possible to inference. True unexplained variation (between-estimate SDs) in the pooled internal–external relationships was extremely large for sRPE vs TD, very large for sRPE vs HSRD, large for sRPE-TL vs HSRD, moderate for sRPE-TL vs VHSRD and AL, and TRIMP vs AL, and small for sRPE-TL vs TD and Impacts, and TRIMP vs HSRD and VHSRD. All other between-estimate SDs were trivial (Table 5).

3.2 Moderating Effects of Training Mode

The relationship between sRPE-TL and TD for Mixed training was possibly very large (r = 0.82; 90% CI 0.75 to 0.87). There were possibly moderate reductions in this correlation magnitude for Skills (change in r when compared with Mixed training = -0.30; 90% CI: -0.61 to 0.08) and Neuromuscular training (-0.42; -0.72 to 0.02). The difference between Mixed and Metabolic training was unclear (-0.08; -0.27 to 0.41). Training mode explained 100% of the between-estimate variance in the relationship between sRPE-TL and TD (R^2_{Meta} = 1.00, τ = 0.00).

The relationship between sRPE-TL and HSRD for Mixed training was possibly large (r = 0.65; 90% CI 0.44 to 0.80). There was a possibly large reduction (change in r when compared with Mixed training = -0.55; 90% CI -0.79 to -0.17) in this correlation magnitude for Neuromuscular training and a possibly moderate reduction for Skills training (-0.29; -0.69 to 0.25). The difference between Mixed and Metabolic training was unclear (-0.21; -0.58 to 0.25). Training mode explained 24% of the between-estimate variance in the relationship between sRPE-TL and HSRD (R^2_{Meta} = 0.24) and the remaining unexplained variation was large (τ = 0.28).

The relationship between sRPE-TL and AL for Mixed training was possibly very large (r = 0.81; 90% CI 0.74 to 0.86). There were possibly large reductions in this correlation magnitude for Skills (change in r when compared with Mixed training = -0.58; 90% CI: -0.73 to -0.37) and Neuromuscular training (-0.55; -0.71 to -0.32), and a likely moderate reduction for Metabolic training (-0.49; -0.66 to -0.28). Training mode explained 100% of the between-estimate variance in the relationship between sRPE-TL and AL (R^2_{Meta} = 1.00, τ = 0.00).

The relationship between TRIMP and AL for Mixed training was possibly very large (r = 0.72; 90% CI 0.55 to 0.84). There was a possibly large reduction in this correlation magnitude for Neuromuscular training (change in r when compared with mixed training = -0.58; 90% CI: -0.79 to -0.25) and a possibly moderate reduction for Skills training (-0.43; -0.72 to -0.01). The difference between Mixed and Metabolic training was unclear (-0.12; -0.48 to 0.28). Training mode explained 100% of the between-estimate variance in the relationship between TRIMP and AL (R^2_{Meta} = 1.00, τ = 0.00).

4.0 DISCUSSION

Associations between internal and external measures of training load and intensity are important in understanding the dose–response nature of team-sport training and competition. These relationships may also provide evidence for the validity of specific internal load measures. Our meta-analysis is the first to provide a quantitative synthesis of such data from 295 athletes and 10418 individual session observations. The main findings from our analyses were that perceived-exertion- and heart-rate-derived measures of internal load show consistently positive associations with running- and accelerometer-derived external loads and intensity during team-sport training and competition, but the magnitude and uncertainty of these relationships is measure and training mode dependent.

The results of our meta-analysis reveal total distance to have the strongest associations with internal load and intensity indicators (Table 5). These data suggest that the internal responses to training and match-play are strongly associated with the amount of running completed—more so than the myriad of other external load measures typically monitored in team-sport athletes. Conceptually, this association seems logical, as the ability to sustain muscle contractions during locomotion is largely dependent on the cumulative provision of substrate and oxygen to the peripheral systems, thereby increasing oxygen consumption and cardiac output [18]. Furthermore, the demands of locomotion are largely driven by central motor commands to the lower-limb and respiratory muscles, to which a neuronal process of the corollary discharge is believed to drive perception of effort [64]. Taken together, these physiological and psychophysical mechanisms create intuitive rationales for the large to very large associations between internal intensity/load and total distance found in our analyses.

It is likely that our other meta-analysed external load and intensity measures are highly dependent on total distance and their relationships with internal load/intensity are partially a consequence of similar mechanisms. Session distances covered above arbitrary high-speed thresholds are strongly associated with session total distance in team-sport athletes [25,65]. The less substantial relationships between these measures and internal load/intensity could, however be, explained by: a) increased measurement error of GPS devices with high movement velocities [66,67], b) individual differences in maximum running velocity or the velocity at which physiologically high-intensities are attained [68,69], or c) the typical non-linear association between running velocity and internal exercise intensity [42,70]. Furthermore, accelerometer-derived load and impacts are likely to be influenced by activities other than locomotion [71] that are commonplace to team-sports, such as some physical collisions, static exertions, jumping, etc. [65,72]. Collectively, these suppositions may explain the findings of our meta-analyses and provide some understanding of the dose–response nature of team-sport training and competition.

Internal training load is a complex and multifactorial construct, making its direct measurement difficult if at all possible using a single modality of assessment [18,73]. Nonetheless, establishing the construct validity and sensitivity of individual measures, such as sRPE-TL and TRIMP, is an important aspect of athlete monitoring [74]. Since the acute biochemical and biomechanical responses to exercise should be associated, in some capacity, with the volume and intensity of the activities performed [1,3,18], internal–external load/intensity relationships provide a means of assessing the construct validity of specific internal measures to be used either in isolation or as part of a more holistic quantification. We provide the first meta-analytic evidence to show that the correlation magnitudes between sRPE-TL and various external load indicators are consistently stronger when compared with the same TRIMP–external load associations in team-sport athletes. Contrary to others [37,38], we believe this provides evidence for the validity of sRPE-TL as an indicator of internal training load in team sport athletes.

The relationships between sRPE and external measures of intensity were of considerably weaker magnitude when compared with external measures of load in our analyses. Several of factors may explain these findings. Firstly, a single measure of external intensity could substantially underrepresented the stochastic movement demands of field- or court-based team-sports that are likely to influence the perception of effort [26]. Frequent changes in movement, characterized by multidirectional high-magnitude accelerations and decelerations, elicit mechanical stress through increased force absorption/production and cause a subsequent increase in metabolic demands that are required to drive muscle contractions even when running at low velocities [18]. This is important, as many additional psychobiological factors such as blood lactate, metabolic acidosis, ventilatory drive, respiratory gases, catecholamines, β-endorphins, and body temperature are also associated with perception of effort during intermittent exercise [41]. Secondly, previous research has established large associations between sRPE and sport-specific non-locomotive activities, such as the number of tackles completed in a rugby league match [34]. Finally, many studies included in our analyses did not state the omission of between-drill rest periods or ball out-of-play time when analysing relative movement demands (i.e. per minute), which could underestimate the true performed external intensities of the training session or match [75,76].

A lack of any ‘near perfect’ association between sRPE (as a measure of intensity or load) and external intensity or load indicators is, of course, not surprising given also the many non-load-related factors that influence an individuals perceived exertion [41]. Indeed, while our analyses do support the construct validity of sRPE, it is plausible that this measure may still lack sensitivity [52] to account for all the highly variable physical demands of team sport training and competition [51,77-79]. Specifically, a global score may be insufficient to accurately appraise the entire range of both physiological and biomechanical exertion signals during exercise [80]. Furthermore, a single gestalt measure of effort perception is likely to be influenced by the most dominant psychophysiological sensation [81]. This effect could be problematic when using sRPE-derived data to inform the planning of training or recovery interventions because the response rates of internal biochemical and mechanical stresses are considerably different [18]. Differential RPE—separate session scores for central and peripheral perceived exertion [33]—may well be a suitable indirect alternative to help mitigate such an issue by separating a players’ perceptions of physiological and biomechanical load [18]. Independent ratings of perceived breathlessness, leg muscle exertion and upper-body muscle exertion have been proposed as a worthwhile addition to internal load monitoring procedures in team sports [33,81,82] and may help both practitioners and researchers further understand the dose–response nature of training and competition [52], changes in fitness [11], fatigue [83], and the risk of injury or illness [10,84].

The strength of internal–external load relations in our meta-analyses encompasses almost an entire magnitude scale, indicating that the unexplained variance between any single measure of internal and external load or intensity could range from ~40–100%. While some of this could be attributed to individual characteristics or simply noise (either measurement error or biological variation), it may well indicate the omission of potentially valuable information contained both within and between training load measures when using a single item to represent internal or external constructs. We have discussed the implications of our findings in relation to the specific measures used, yet our data could also support the notion that multiple measures are needed to accurately quantify internal and external training loads in team sports [31,32,73]. Since it is already common practice to routinely collect several training load measures [85]—which are often based on perceived clinical or practical importance [26]—a pertinent challenge is understanding the most parsimonious and statistically sound variable selection that best represent ‘internal’ and ‘external’ constructs for the differing training modes undertaken by team-sport athletes [31,32].

Our analyses revealed much stronger internal–external load relationships (e.g. sRPE-TL and TD) in comparison to the corresponding internal–external intensity relationships (e.g. sRPE and TD per min). This potentially indicates an issue of mathematical coupling—the effect occurring when one variable directly or indirectly contains the whole or part of the other and the two variables are analysed using standard correlation or regression techniques [86]. Mathematical coupling can result in correlations that appear far more substantial than any true biological/physiological association between the two variables [87]. In the context of training monitoring, internal and external loads are not mathematically distinct from one another since session volume is a constant factor within both constructs. We feel that this represents an important yet overlooked issue within training monitoring that may extend to many analyses of training load. Practitioners and researchers should therefore be aware and cautious of this fact to avoid making erroneous conclusions when interpreting data on individuals or from research.

There was considerable uncertainty (ranging up to extremely large in magnitude) in the SDs representing true between-estimate variation in some of our meta-analysed internal–external load and intensity relationships. This could suggest that team-sport athletes' internal responses to training and competition are multifactorial and influenced by several factors. Our meta-regression analyses indicated substantial moderating effects of training mode on the sRPE-TL–TD, sRPE-TL–HSRD, sRPE-TL–AL and TRIMP–AL relationships. Here, training mode explained 25–100% of the observed between-estimate heterogeneity when compared with the unadjusted pooled estimates (i.e. all training modes combined). Internal–external load relationships were typically weaker when concentrating on discrete training modes. This could indicate that the correlations in the unadjusted analyses (combining multiple training modes) are spuriously high and only confirm already obvious differences between homogeneous subsets [88], such as the difference in internal and external loads between disparate training typologies.

Our defined training modes primarily differ in output goals, which influences the structure and selection of training activities along with the associated work-rest ratios. It is possible that these discrepancies explain the moderating effects of training mode observed on the relationships between internal and external training load in our present analyses. Reductions in work-to-rest ratio during small-sided gameplay have previously been shown to increase heart rate in spite of reduced distances covered at high- and very-high speeds [89], while the addition of physical collisions during repeated sprint exercise has shown to markedly increase internal loads for the same distances covered [90]. Furthermore, training modes utilising closed kinetic chain exercises (typical to neuromuscular conditioning) often require high levels of force and velocity to be produced or resisted [91,92], resulting in frequent bouts of peripherally demanding activities that can be independent of locomotion [72]. Here, an uncoupling of the relationship between internal and external loads could be a consequence of insensitivity in the specific measures used [81]. In agreement with previous research [31], these results imply that internal–external load relations are specific to the mode of training and the load measures that best represent one training mode may not do so for others.

There are several limitations with our current meta-analysis that could largely be the consequence of varied data collection and reporting from our included studies. This is inevitable when synthesising data from unstructured observational research designs that are not governed by strict reporting standards such observational epidemiological studies (e.g. STROBE) or randomized controlled trials (e.g. CONSORT) [93]. We grouped our internal and external measures of load and intensity measures based on their constructs as a means of providing a more concise analysis that met our research aims. Despite this, some measurement methods (e.g. CR100-derived sRPE or individualised TRIMP) clearly show improved sensitivity and precision over their traditional counterparts [94,95]. The grouping of external loads between different manufacturers has notable flaws, particularly with the variety of sampling rates, chipsets, filtering methods and data processing algorithms observed between athlete tracking devices [93]. A key discrepancy between our included studies was the mixed correlation calculation methods, with some studies reporting within-athlete correlations and others pooling their repeated measures as though all the data were drawn from a single sample. Finally, our relatively low number of estimates per dataset restricted any examination of the many other factors that may reasonably moderate the relationships between internal and external training loads/intensity in team-sport athletes.

We propose several suggestions for practitioners wishing to analyse their training load data as a means of assuring an evidenced-based approach to the delivery of performance-focused outcomes. A knowledge of the specific internal responses associated with various external training doses has the potential to enhance training evaluation, prescription, periodization and athlete management through a detailed assessment of training fidelity and efficacy [17,19,20]. Specifically, changes in internal load with respect to a standard external load may be used to infer on an athletes fitness or fatigue over time or in comparison to their peers [14]. The simplicity of using an external:internal load ratio to provide a normalised metric that may be indicative of fitness or fatigue is conceptually appealing [83,96-99] and lends to dashboard-level analyses. This approach violates fundamental theoretical and empirical assumptions inherent to ratios [100,101], however, since we demonstrate that internal–external load relationships are substantially disproportionate. To avoid this leading to errors in interpreting training loads on individual athletes [100], we recommend that practitioners avoid ratios and look to independently analyse continuous measures of internal and external load using a more progressive approach. This could include the assessment of individual changes in daily, weekly or cumulative load [102] that are meaningful and free from typical or random variation [103,104] that is inherent to training load in team-sport athletes [33,81]. For the retrospective analyses of larger datasets, we again recommend that ratios are avoided and that practitioners seek to explore their data through more appropriate means. These may include, but are not limited to: within- [48] or between-athlete [105] correlations, generalized estimating equations [100], mixed effect linear modelling [106] or dimension reduction techniques (e.g. principal component analysis [31,32].

The wide magnitude dispersion and relative lack of precision in some of our meta-analysed correlation coefficients would suggest that further research is warranted to improve the understanding of internal–external load relationships in team sport athletes. We recommend that such work should aim to explore the reasons why this dispersion and imprecision exists, rather than simply if a relationship is evident. The substantial moderating effects of training mode in our analyses indicate that any such research should be conducted on homogeneous subsets of training activities, rather than combining several diverse training modes. Further examination of other conceptual and technical moderating factors, such as specific fitness qualities, athlete experience, fatigue, prior training load, measurement, and the magnitude of load may also prove to be useful. The inevitable repeated measures nature of this work should be met with the appropriate analyses to avoid inference error arising from pseudoreplication [107]. Furthermore, we recommend issues of mathematical coupling should be appropriately considered and avoided. Finally, in agreement with others, we encourage the collection of differential RPE in both research and practice as a means of separating an athlete’s perception of physiological and biomechanical internal loads to help further understand the dose–response nature of team-sport training.

5.0 CONCLUSIONS

Our study is the first to provide a quantitative synthesis of evidence examine the relationships between internal and external measures of load and intensity during team-sport training and competition. While such associations appear consistently positive, their magnitudes are dependent on the specific measures used and are substantially moderated by training mode. Total running distance appears to have the strongest association with internal training load and intensity, and the relationships with measures of external load are stronger with sRPE-TL when compared with TRIMP. Our findings have implications for the dose–response nature of team-sport training and competition as well as the measurement of internal load. Further work is recommended to improve the accuracy in measuring internal load in team-sport athletes.

DECLARATIONS

Compliance with Ethical Standards

Funding

No sources of funding or financial support were used to assist in the preparation of this article.

Conflict of Interest

Shaun J. McLaren, Tom W. Macpherson, Aaron J. Coutts, Christopher Hurst, Iain R. Spears and Matthew Weston declare they have no conflict of interest relevant to the content of this article.

Acknowledgments

We would like to express our gratitude to the authors who kindly provided additional data for the studies included in this meta-analysis. We are extremely grateful to Professor Greg Atkinson for his useful scientific discussions and statistical advice during the preparation of the paper.

REFERENCES

1. Impellizzeri FM, Rampinini E, Marcora SM. Physiological assessment of aerobic training in soccer. J Sports Sci. 2005;23:583–92.

2. Iaia FM, Rampinini E, Bangsbo J. High-intensity training in football. Int J Sports Physiol Perform. 2009;4:291–306.

3. Coffey VG, Hawley JA. The molecular bases of training adaptation. Sports Med. 2007;37:737–63.

4. Foster C, Florhaug JA, Franklin J, Gottschall L, Hrovatin LA, Parker S, Doleshal P, Dodge C. A new approach to monitoring exercise training. J Strength Cond Res. 2001;15:109–15.

5. Soligard T, Schwellnus M, Alonso JM, Bahr R, Clarsen B, Dijkstra HP, Gabbett T, Gleeson M, Hägglund M, Hutchinson MR, Van Rensburg CJ. How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. Br J Sports Med. 2016;50:1030–41.

6. Schwellnus M, Soligard T, Alonso JM, Bahr R, Clarsen B, Dijkstra HP, Gabbett TJ, Gleeson M, Hägglund M, Hutchinson MR, Van Rensburg CJ. How much is too much? (Part 2) International Olympic Committee consensus statement on load in sport and risk of illness. Br J Sports Med. 2016;50:1043–52.

7. Halson SL. Monitoring training load to understand fatigue in athletes. Sports Med. 2014;44:139–47.

8. Gabbett TJ. The training-injury prevention paradox: should athletes be training smarter and harder?. Br J Sports Med. 2016;50:273–80.

9. Drew MK, Finch CF. The relationship between training load and injury, illness and soreness: A systematic and literature review. Sports Med. 2016;46:861–83.

10. Jones CM, Griffiths PC, Mellalieu SD. Training load and fatigue marker associations with injury and illness: A systematic review of longitudinal studies. Sports Med. 2016;108:113.

11. Jaspers A, Brink MS, Probst SGM, Frencken WGP, Helsen WF. Relationships between training load indicators and training outcomes in professional soccer. Sports Med. 2016;47:533–44.

12. Gabbett TJ, Whyte DG, Hartwig TB, Wescombe H, Naughton GA. The relationship between workloads, physical performance, injury and illness in adolescent male football players. 2014;44:989–1003.

13. Quarrie KL, Raftery M, Blackie J, Cook CJ, Fuller CW, Gabbett TJ, Gray AJ, Gill N, Hennessy L, Kemp S, Lambert M. Managing player load in professional rugby union: a review of current knowledge and practices. Br J Sports Med. 2017;51:421–7.

14. Bourdon PC, Cardinale M, Murray A, Gastin P, Kellmann M, Varley MC, Gabbett TJ, Coutts AJ, Burgess DJ, Gregson W, Cable NT. Monitoring athlete training loads: Consensus statement. Int J Sports Physiol Perform. 2017;12:S2–161–S2–170.

15. Robertson S, Bartlett JD, Gastin PB. Red, Amber, or Green? Athlete Monitoring in Team Sport: The Need for Decision-Support Systems. Int J Sports Physiol Perform. 2017;12:S2–73–S2–79.

16. Gabbett HT, Windt J, Gabbett TJ. Cost-benefit analysis underlies training decisions in elite sport. Br J Sports Med. 2016;50:1291–2.

17. Burgess DJ. The research doesn't always apply: Practical solutions to evidence-based training-load monitoring in elite team sports. Int J Sports Physiol Perform. 2017;12:S2–136–S2–141.

18. Vanrenterghem J, Nedergaard NJ, Robinson MA, Drust B. Training load monitoring in team sports: A novel framework separating physiological and biomechanical load-adaptation pathways. Sports Med. 3rd ed. 2017;110:1495.

19. Bartlett JD, O'Connor F, Pitchford N, Torres-Ronda L, Robertson SJ. Relationships between internal and external training load in team sport athletes: evidence for an individualised approach. Int J Sports Physiol Perform. 2017;12(2):230–4.

20. Taylor KL, Weston M, Batterham AM. Evaluating intervention fidelity: An example from a high-intensity interval training study. Piacentini MF, editor. PLoS ONE. 2015;10:e0125166.

21. Castillo D, Weston M, McLaren SJ, Cámara J, Yanci J. Relationships between internal and external match load indicators in soccer match officials. Int J Sports Physiol Perform. 2016; doi: 10.1123/ijspp.2016-0392

22. Lovell TWJ, Sirotic AC, Impellizzeri FM, Coutts AJ. Factors affecting perception of effort (session rating of perceived exertion) during rugby league training. Int J Sports Physiol Perform. 2013;8:62–9.

23. Casamichana D, Castellano J. The relationship between intensity indicators in small-sided soccer games. J Hum Kinet. 2015;46:119–28.

24. Casamichana D, Castellano J, Calleja-González J, San Román J, Castagna C. Relationship between indicators of training load in soccer players. J Strength Cond Res. 2013;27:369–74.

25. Gallo T, Cormack S, Gabbett T, Williams M, Lorenzen C. Characteristics impacting on session rating of perceived exertion training load in Australian footballers. J Sports Sci. 2015;33:467–75.

26. Gaudino P, Iaia FM, Strudwick AJ, Hawkins RD, Alberti G, Atkinson G, Gregson W. Factors influencing perception of effort (session rating of perceived exertion) during elite soccer training. Int J Sports Physiol Perform. 2015;10:860–4.

27. Pustina AA, Sato K, Liu C, Kavanaugh AA, Sams ML, Liu J, Uptmore KD, Stone MH. Establishing a duration standard for the calculation of session rating of perceived exertion in NCAA division I men's soccer. Journal of Trainology. 2017;6:26–30.

28. Scanlan AT, Wen N, Tucker PS, Dalbo VJ. The Relationships Between Internal and External Training Load Models During Basketball Training. J Strength Cond Res. 2014;28:2397–405.

29. Scott BR, Lockie RG, Knight TJ, Clark AC, Janse de Jonge XAK. A comparison of methods to quantify the in-season training load of professional soccer players. Int J Sports Physiol Perform. 2013;8:195–202.

30. Scott TJ, Black CR, Quinn J, Coutts AJ. Validity and reliability of the session-RPE method for quantifying training in Australian football: A comparison of the CR10 and CR100 scales. J Strength Cond Res. 2013;27:270–6.

31. Weaving D, Marshall P, Earle K, Nevill A, Abt G. Combining internal- and external-training-load measures in professional rugby league. Int J Sports Physiol Perform. 2014;9:905–12.

32. Weaving D, Jones B, Till K, Marshall P, Abt G. Multiple measures are needed to quantify training loads in professional rugby league. Int J Sports Med. 2017; 38:735–40

33. Weston M, Siegler J, Bahnert A, McBrien J, Lovell R. The application of differential ratings of perceived exertion to Australian Football League matches. 2015;18:704–8

34. Coutts AJ, Sirotic AC, Knowles H, Catterick C. Monitoring training loads in professional rugby league. In: Reilly T, Korkusuz F, editors. Science and football VI: the proceedings of the Sixth World Congress on Science and Football. London: Routledge; 2008. pp. 272–7.

35. Silva P, Santos ED, Grishin M, Rocha JM. Validity of heart rate-based indices to measure training load and intensity in elite football players. J Strength Cond Res. 2017; doi:10.1519/JSC.0000000000002057

36. Sparks M, Coetzee B, Gabbett TJ. Internal and external match loads of university-level soccer players. J Strength Cond Res. 2017;31:1072–7.

37. Nassis GP, Gabbett TJ. Is workload associated with injuries and performance in elite football? A call for action. Br J Sports Med. 2017;51:486–7.

38. Lambert MI, Borresen J. Measuring training load in sports. Int J Sports Physiol Perform. 2010;5:406–11.

39. Moher D, Liberati A, Tetzlaff J, Altman DG. The Prima Group (2009) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med. 2009;6:e1000097.

40. Groslambert A, Mahon AD. Perceived exertion: influence of age and cognitive development. Sports Med. 2006;36:911–28.

41. Robertson RJ, Noble BJ. Perception of physical exertion: methods, mediators, and applications. Exerc Sport Sci Rev. 1997;25:407–52.

42. Borg G, Borg E. A new generation of scaling methods: Level-anchored ratio scaling. Psychologica. 2001;28:15–45.

43. Impellizzeri FM, Borg E, Coutts AJ. Intersubjective comparisons are possible with an accurate use of the Borg CR scales. Int J Sports Physiol Perform. 2011;6:2–7.

44. Banister EW. Modeling elite athletic performance. In: MacDougall JD, Wenger HA, Green HJ, editors. Physiological testing of the high performance athlete. 2nd ed. Champaign: Human Kinetics Books. 1991. pp. 403–24.

45. Edwards S. High performance training and racing. Edwards S, editor. The heart rate monitor book. Sacramento: Feet Fleet Press. 1993. pp. 113–23.

46. Manzi V, Iellamo F, Impellizzeri F, D'Ottavio S, Castagna C. Relation between individualized training impulses and performance in distance runners. Med Sci Sports Exerc. 2009;41:2090–6.

47. Senn SJ. Overstating the evidence – double counting in meta-analysis and related problems. BMC Med Res Methodol. 2009;9:10.

48. Bland MJ, Altman DG. Statistics notes: Calculating correlation coefficients with repeated observations: Part 1—correlation within subjects. BMJ. 1995;310:446.

49. Bland MJ, Altman DG. Statistics Notes: Correlation, regression, and repeated data. BMJ. 1994;308:896.

50. Pyne DB. Multidisciplinary and collaborative research in sports physiology and performance. Int J Sports Physiol Perform. 2012;7:1.

51. McLaren SJ, Weston M, Smith A, Cramb R, Portas MD. Variability of physical performance and player match loads in professional rugby union. J Sci Med Sport. 2016;19:493–7.

52. Weston M. Difficulties in determining the dose-response nature of competitive soccer matches. J Athl Enhanc. 2013;02:1–2.

53. Persaud R, Bland MJ, Altman DG. Correlation, regression, and repeated data. BMJ. 1994;308:1510.

54. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc. 2009;41:3–13.

55. Knapp G, Hartung J. Improved tests for a random effects meta-regression with a single covariate. Statistics in medicine. 2003;22:2693–710.

56. Higgins JPT. Commentary: Heterogeneity in meta-analysis should be expected and appropriately quantified. Int J Epidemiol. 2008;37:1158–60.

57. DerSimonian R, Laird N. Meta-analysis in clinical trials. Controlled clinical trials. 1986;7:177–88.

58. Higgins JPT, Green S. Cochrane handbook for systematic reviews of interventions. Chichester: John Wiley & Sons; 2008.

59. Aloe AM, Becker BJ, Pigott TD. An alternative to R2 for assessing linear models of effect size. Research Synthesis Methods.2010;1:272–83.

60. Batterham AM, Hopkins WG. Making meaningful inferences about magnitudes. Int J Sports Physiol Perform. 2006;1:50–7.

61. Hopkins WG. A spreadsheet for deriving a confidence interval, mechanistic inference and clinical inference from a P value. Sportscience. 2007;11:16–21.

62. Fisher RA. On the probable error of a coefficient of correlation deduced from a small sample. Metron. 1921;1:3–32.

63. Smith TB, Hopkins WG. Variability and predictability of finals times of elite rowers. Med Sci Sports Exerc. 2011;43:2155–60.

64. Marcora S. Perception of effort during exercise is independent of afferent feedback from skeletal muscles, heart, and lungs. J Appl Physiol. 2009;106:2060–2.

65. Gabbett TJ. Relationship between accelerometer load, collisions, and repeated high-intensity effort activity in rugby league players. J Strength Cond Res. 2015;29:3424–31.

66. Rampinini E, Alberti G, Fiorenza M, Riggio M, Sassi R, Borges TO, Coutts AJ. Accuracy of GPS devices for measuring high-intensity running in field-based team sports. Int J Sports Med. 2015;36:49–53.

67. Johnston RJ, Watsford ML, Kelly SJ, Pine MJ, Spurrs RW. Validity and interunit reliability of 10 Hz and 15 Hz GPS units for assessing athlete movement demands. J Strength Cond Res. 2014;28:1649–55.

68. Buchheit M, Laursen PB. High-intensity interval training, solutions to the programming puzzle. Part I: Cardiopulmonary emphasis. Sports Med. 2013;43:313–38.

69. Abt G, Lovell R. The use of individualized speed and intensity thresholds for determining the distance run at high-intensity in professional soccer. J Sports Sci. 2009;27:893–8.

70. Faude O, Kindermann W, Meyer T. Lactate threshold concepts: how valid are they? Sports Med. 2009;39:469–90.

71. Boyd LJ, Ball K, Aughey RJ. Quantifying external load in Australian football matches and training using accelerometers. Int J Sports Physiol Perform. 2013;8:44–51.

72. Roe G, Halkier M, Beggs C, Till K, Jones B. The use of accelerometers to quantify collisions and running demands of rugby union match-play. Int J Perf Anal Spor. 2016;16:590–601.

73. Cardinale M, Varley MC. Wearable training-monitoring technology: Applications, challenges, and opportunities. Int J Sports Physiol Perform. 2017;12:S2–55–S2–62.

74. Robertson S, Kremer P, Aisbett B, Tran J, Cerin E. Consensus on measurement properties and feasibility of performance tests for the exercise and sport sciences: A Delphi study. Sports Med Open. 2017;3:2. doi:10.1186/s40798-016-0071-y

75. White AD, MacFarlane N. Time-on-pitch or full-game GPS analysis procedures for elite field hockey? Int J Sports Physiol Perform. 2013;8:549–55.

76. Gabbett TJ. Influence of ball-in-play time on the activity profiles of rugby league match-play. J Strength Cond Res. 2015;29:716–21.

77. Gregson W, Drust B, Atkinson G, Di Salvo V. Match-to-match variability of high-speed activities in Premier League soccer. Int J Sports Med. 2010;31:237–42.

78. Kempton T, Sirotic AC, Coutts AJ. Between match variation in professional rugby league competition. J Sci Med Sport. 2014;7:404–7.

79. Kempton T, Sullivan C, Bilsborough JC, Cordy J, Coutts AJ. Match-to-match variation in physical activity and technical skill measures in professional Australian Football. J Sci Med Sport. 2015;18:109–13.

80. Hutchinson JC, Tenenbaum G. Perceived effort — Can it be considered gestalt? Psychology of Sport and Exercise. 2006;7:463–76.

81. McLaren SJ, Smith A, Spears IR, Weston M. A detailed quantification of differential ratings of perceived exertion during team-sport training. J Sci Med Sport. 2017;20:290–5.

82. McLaren SJ, Graham M, Spears IR, Weston M. The sensitivity of differential ratings of perceived exertion as measures of internal load. Int J Sports Physiol Perform. 2016 Apr;11(3):404–6.

83. Gallo TF, Cormack SJ, Gabbett TJ, Lorenzen CH. Pre-training perceived wellness impacts training output in Australian football players. J Sports Sci. 2015;34:1445–51.

84. Ritchie D, Hopkins WG, Buchheit M, Cordy J, Bartlett JD. Quantification of training load during return to play following upper and lower body injury in Australian Rules football. Int J Sports Physiol Perform. 2017;12:634–41.

85. Akenhead R, Nassis GP. Training load and player monitoring in high-level football: Current practice and perceptions. Int J Sports Physiol Perform 2016;11:587–93.

86. Archie JP. Mathematic coupling of data: a common source of error. Ann Surg. 1981;193:296–303.

87. Pearson K. On a form of spurious correlation which may arise when indices are used in the measurement of organs. Proc R Soc London. 1896;60:489–502.

88. Atkinson G, Nevill AM. Selected issues in the design and analysis of sport performance research. J Sports Sci. 2001;19:811–27.

89. Malone S, Hughes B, Collins K. The influence of exercise to rest ratios on physical and physiological performance during hurling specific small-sided games. J Strength Cond Res. 2017; doi:10.1519/JSC.0000000000001887

90. Johnston RD, Gabbett TJ. Repeated-sprint and effort ability in rugby league players. J Strength Cond Res. 2011;25:2789–95.

91. Milburn PD. The kinetics of rugby union scrummaging. J Sports Sci. 2008;8:47–60.

92. Kraemer WJ, Vescovi JD, Dixon P. The physiological basis of wrestling: Implications for conditioning programs. Natl Strength Cond Assoc J. 2004;26:10–5.

93. Malone JJ, Lovell R, Varley MC, Coutts AJ. Unpacking the Black Box: Applications and Considerations for Using GPS Devices in Sport. Int J Sports Physiol Perform. 2017;12:S2–18–S2–26.

94. Fanchini M, Ferraresi I, Modena R, Schena F, Coutts AJ, Impellizzeri FM. Use of the CR100 scale for session rating of perceived exertion in soccer and its interchangeability with the CR10. Int J Sports Physiol Perform. 2016;11:388–92.

95. Akubat I, Patel E, Barrett S, Abt G. Methods of monitoring the training and match load and their relationship to changes in fitness in professional youth soccer players. J Sports Sci. 2012;30:1473–80.

96. Malone S, Doran D, Akubat I, Collins K. The integration of internal and external training load metrics in hurling. J Hum Kinet. 2016;53:1–11.

97. Torreño N, Munguía-Izquierdo D, Coutts AJ, de Villarreal ES, Asian-Clemente J, Suarez-Arrones L. Relationship between external and internal loads of professional soccer players during full matches in official games using global positioning systems and heart-rate technology. Int J Sports Physiol Perform. 2016;11:940–6.

98. Suarez-Arrones L, Torreño N, Requena B, Sáez De Villarreal E, Casamichana D, Barbero-Alvarez JC, Munguia-Izquierdo D. Match-play activity profile in professional soccer players during official games and the relationship between external and internal load. J Sports Med Phys Fitness. 2015;55:1417–22.

99. Akubat I, Barrett S, Abt G. Integrating the internal and external training loads in soccer. Int J Sports Physiol Perform. 2014;9:457–62.

100. Atkinson G, Batterham A. The use of ratios and percentage changes in sports medicine: time for a rethink?. Int J Sports Med. 2012;33:505–6.

101. Tanner JM. Fallacy of per-weight and per-surface area standards, and their relation to spurious correlation. J Appl Physiol. 1949;2:1–15.

102. Williams S, Trewartha G, Cross MJ, Kemp SPT, Stokes KA. Monitoring what matters: A systematic process for selecting training-load measures. Int J Sports Physiol Perform. 2017;12:S2–101–S2–106.

103. Atkinson G, Batterham AM. True and false interindividual differences in the physiological response to an intervention. Exp. Physiol. 2015;100:577–88.

104. Hopkins WG. Individual responses made easy. J Appl Physiol. 2015;118:1444–6.

105. Bland MJ, Altman DG. Statistics notes: Calculating correlation coefficients with repeated observations: Part 2—correlation between subjects. BMJ. 1995;310:633.

106. Vandenbogaerde TJ, Hopkins WG. Monitoring acute effects on athletic performance with mixed linear modeling. Med Sci Sports Exerc. 2010;42:1339–44.

107. Lazic SE. The problem of pseudoreplication in neuroscientific studies: Is it affecting your analysis? BMC Neurosci. 2010;11:5.

TABLES AND FIGURES

Figure 1. Flow diagram of the study, dataset and estimate selection process.

[Footnote]

*Refer to Table 2.

**estimates from the same study describing the same relationship for a grouped construct (e.g. TRIMP vs TD using both Banisters TRIMP and Edwards TRIMP, or using separate within-athlete and partial correlation analyses) or training mode (e.g. all training modes combined and within a discrete training mode metabolic conditioning)

***< 2 datasets from < 2 independent studies describing a relationship between internal and external load/intensity.

Abbreviations: sRPE: session rating of perceived exertion, sRPE-TL: session rating of perceived exertion training load, TRIMP: heart-rate-derived training impulse, TD: total distance covered, HSRD: distance covered at high speeds (≥ 13.1–15.0 km·h^{-1}), VHSRD: distance covered at very high speeds (≥ 16.9–19.8 km·h^{-1}), AL: accelerometer-derived load, Impacts: total number of sustained impacts (> 2–5 G).